Political Attitudes, Partisanship, and Merger Activity[*]

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Abstract

Using detailed data on employees' campaign contributions to Democrats and Republicans, we find that firms are considerably more likely to announce and complete a merger when their political attitudes are closer. Furthermore, acquisition announcement returns and post-merger performance are higher when employees have more similar political attitudes. The effects are stronger when political polarization is greater, during economic expansions, and when the target and acquirer plan to integrate operations. The effect of political attitudes is distinct from that of corporate culture. Overall, we provide new estimates that political attitudes and polarization affect the allocation of real assets in the economy.

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1. Introduction

This paper studies a new channel, unexplored by previous studies, through which corporate political attitudes and political partisanship affect one of the firm's most important investment decisions – mergers and acquisitions. Rather than focusing on firms' direct dealings with politicians and government officials, we explore the role of the political divergence or similarity between potential acquirers and targets, as reflected by their employees' personal contributions to political campaigns of Democrats and Republicans. The resulting estimates provide novel evidence on the real effects of political attitudes and partisanship on the allocation of assets in the economy.

A growing body of research studies the increase in political partisanship and polarization in the U.S. (e.g., McCarty, Poole, and Rosenthal (2006); Iyengar, Sood, and Lelkes (2012); Mason (2013, 2015); Lott and Hassett (2014); Gentzkow (2016); Boxell, Gentzkow, and Shapiro (2017); Autor, Dorn, Hanson, and Majlesi (2020)) and its implications for the behavior of households (e.g., Makridis (2022); McGrath (2017); Mian, Sufi, and Khoshkhou (2018); Meeuwis, Parker, Schoar, and Simester (2021)), judges (e.g., Posner (2008), McKenzie (2012), and Chen (2020)), and credit analysts (Kempf and Tsoutsoura (2021)). These studies explore the effects of political partisanship using the variation in unilateral decisions of individual agents whose perceptions and economic outlook are influenced by the dichotomy of whether the President is from the party they support.

In contrast, this paper investigates the role of political partisanship in bilateral corporate decisions – mergers and acquisitions – a setting where political partisanship is measured directly across the two interested counterparties (the acquirer and the target) and can influence both ex-ante deal formation and ex-post integration and outcomes. An additional benefit of this setting is that the distance between the political attitudes of the acquirer and the target offers continuous variation in political partisanship rather than the discrete variation of the President's party used in many prior studies.

We aim to answer four main questions: (1) How does the political distance between firms affect the likelihood of mergers and acquisitions? (2) How does variation in political polarization and economic conditions over time affect the role of political attitudes in mergers and acquisitions? (3) What are the implications of political attitudes for merger negotiations, announcement returns, and post-merger integration and performance? (4) How does the role of political distance differ from that of other dimensions of corporate culture?

To answer these questions, we hand-collect detailed data on the personal contributions of corporate employees to political campaigns from 1978-2021. These data include a total of 4,310,589 contributions from 501,741 employees of 9,253 firms, which average $9,301 per firm each year, of which $5,034 is contributed to Democrats and $4,268 to Republicans. Using these data, we measure a firm's political attitude as the ratio of the total number of employee contributions to Democratic campaigns to the total number of contributions to both Democratic and Republican campaigns over an 8-year-rolling window. By focusing on the personal contributions of a firm's entire labor force, which is dominated by rank-and-file employees who are uninvolved in merger decisions, and purging the estimates 8 years back, we generate estimates that are largely free from concerns that contributions are contemporaneously or endogenously related to mergers through channels different from political partisanship, or that they reflect firms' merger-related strategic behavior. Using this measure of firms' political attitudes, we construct a pairwise measure of the political distance between any two firms, labeled *Political Distance*, which equals the absolute value of the difference between their political attitudes.

In the first set of analyses, we investigate the effect of the political distance between firms on the likelihood of a merger. Following the method of Bena and Li (2014), we estimate the likelihood of mergers and acquisitions by generating synthetic (or pseudo) acquirers and targets for each merger in our sample of 2,325 mergers from 1985-2021. We implement this procedure using three different matching rules. First, we match each acquirer and target with random firms.

Second, we match each acquirer and target with industry- and size-matched firms. Third, we match each acquirer and target with industry-, size-, and book-to-market-matched firms.

Across all matched samples, we find that greater political distance between firms reduces the likelihood of a future merger announcement. The estimates are economically meaningful and imply that an increase of one standard deviation in the political distance between firms reduces the likelihood of a merger by 0.59 to 1.34 percentage points (or 6.4% to 14.6% relative to the sample-mean pseudo-likelihood of 9.18%). These estimates are statistically significant in all specifications, and they hold robustly after controlling for geographic proximity, acquirer/target characteristics, and after including industry-by-year and deal fixed effects.

A natural question that arises is how political differences between acquirers and targets differ from other corporate cultural differences. It is increasingly clear that people supporting different political parties often have fundamentally different views about policies on taxation, labor, markets, fair compensation, and even whether firms should seek contracts with the government, in particular the defense department.[2] Existing research shows that unlike cultural or other social divides, where group-related attitudes are constrained by social norms, there are no corresponding pressures to temper disapproval of political opponents (e.g., Himmelfarb and Lickteig (1982); Iyengar and Westwood (2015); Maccoby and Maccoby (1954); Sigall and Page (1971)). Hence, we posit that the effects of political partisanship likely are distinct from, and add to, those of other cultural differences.

To test this hypothesis, we re-estimate the analyses in a subsample that includes measures of cultural distances across five aspects of corporate culture -- Innovation, Integrity, Quality, Respect, and Teamwork – adopted from Li, Mai, Shen, and Yan (2020).[3] The estimates suggest

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[2] See, for example, "Google Wants to Do Business With the Military—Many of Its Employees Don't," by Joshua Brustein and Mark Bergen, https://www.bloomberg.com/features/2019-google-military-contract-dilemma/.

[3] We thank Kai Li, Feng Mai, Rui Shen, and Xinyan Yan for sharing their corporate culture data with us.

that political distance has little correlation with any of the cultural distance measures. Further, the effect of political distance on the likelihood of merger announcements remains equally important, both economically and statistically, after controlling for corporate cultural differences.

Taken together, these findings suggest that political differences across firms are a strong, distinctive predictor of future mergers. As such, they provide a new channel for the rise of politics in the workplace and the decline in political diversity inside firms (See, for example, "Politics are becoming tougher to avoid at work, survey finds", *The Washington Post*, October 5, 2022).

In the second set of analyses, we explore the role of the variation in political polarization and economic conditions in the United States over time. We conjecture that the effects of the political distance between acquirers and targets should be stronger when the political divide is more pronounced. To test this conjecture, we use two measures of political polarization. The first measure, *PCI,* is based on the Political Conflict Index constructed by Azzimonti (2018). The second measure, the *House Partisanship Index* (*HPI*), is based on voting data from the U.S. House of Representatives. Using both measures, the estimates indicate that the effects of political partisanship on merger likelihood are more pronounced when political polarization is higher, suggesting that polarization exacerbates the effect of political attitudes. This set of results also helps rule out alternative explanations for the measured effect of political differences, since the magnitude of the effect varies with nationwide political polarization.

We also explore the effects of the variation in economic conditions over time. We conjecture that political distance plays a weaker role in merger formation during recessions for two reasons. First, political polarization tends to be lower during recessions (e.g., Stanig (2013)). Indeed, we find that both *PCI* and *HPI* are lower during NBER recessions. Second, recession mergers are often "necessity" mergers aimed to allow the merging firms to restructure, downsize, and continue operating (e.g., Dutz (1989), Jensen (1993), Mitchell and Mulherin (1996)). As such, firms might put aside their political and ideological differences. Consistent with this hypothesis, we find that the effect of political distance on merger likelihood is only economically and statistically significant outside recessions.

In the third set of analyses, we attempt to provide evidence on the mechanisms through which political partisanship affects the likelihood of mergers and acquisitions. First, we hypothesize that differences in political alignment can create costs in post-merger integration. These differences, however, are less relevant if the acquirer and target are not planning to integrate their businesses. To test this hypothesis, we search the merging firms' SEC filings for words related to integration. We then re-estimate the effects of political distance on merger likelihood for firms that emphasize integration in their post-merger filings and those that do not. The estimates suggest that political differences more negatively affect merger likelihood when the companies plan to integrate their operations.

Second, we hypothesize that political distance can affect the success of the merger negotiations themselves. We find that the likelihood of deal completion in announced mergers is significantly lower when the political distance between the acquirer and the target is greater. An increase of one standard deviation in the political distance between the acquirer and the target increases the likelihood of deal failure by 2.03 to 2.33 percentage points, or 12.4% to 14.3% relative to the sample-mean likelihood of 16.3%. We also find that the likelihood of a hostile or unsolicited bid is significantly greater when the political distance between the acquirer and the target is higher. An increase of one standard deviation in political distance increases the likelihood of a hostile bid by 1.25 to 1.77 percentage points, or 10.2% to 14.3% relative to the sample-mean of 12.4%. Together, these results imply that the greater the political distance between acquirers and targets is, the more likely merger negotiations are to break down, resulting in incomplete deals or hostile takeovers.

In the last set of analyses, we investigate the effects of the political distance between acquirers and targets on merger performance. We start by studying acquisition announcement returns. The estimates suggest that the combined announcement returns are lower when the political distance is higher. The effects are economically nontrivial and statistically significant. An increase of one standard deviation in political distance reduces cumulative abnormal returns at merger announcement by 34.8 to 42.9 basis points. We also investigate the effects of political distance on post-merger performance in completed deals. We find that in the years following a merger completion, *ROA* is lower when the political distance is greater. An increase of one standard deviation in political distance reduces three-year average *ROA* by 0.56% to 0.67%, and these estimates are statistically significant at the 5% level. We also find that an increase of one standard deviation in political distance reduces the 3-year CAPM buy-and-hold abnormal return by 9.5% to 12.8%, and these estimates are statistically significant at the 10% level.

Collectively, these findings indicate that political divergence between acquirers and targets has negative consequences for merger performance and value. An important caveat, however, is that these estimates likely underestimate the true effect of political partisanship on integration because, as we have shown, politically misaligned firms are less likely to merge in the first place.

Overall, our paper contributes to a large body of research that studies the determinants and consequences of mergers. Some researchers focus on the value-maximizing attributes of mergers (e.g., Matsusaka (2001); Jovanovic and Braguinsky (2004)), while others study inefficiencies, possibly driven by agency conflicts (e.g., Baumol (1959); Jensen (1986, 1993); Stulz (1990)) or hubris (Roll (1986)). Our paper adds to this literature by showing that the political fit between acquirers and targets is an important predictor of merger success, performance, and value.

Our paper is also broadly related to prior studies of the relation between politics and mergers and acquisitions. Holburn and Bergh (2014) show that mergers in regulated industries are preceded by increases in election campaign contributions to influence regulatory merger approvals. Dinc and Erel (2013) provide evidence on the involvement of European governments in acquisitions to keep target companies domestically owned. Aktas, de Bodt, and Roll (2004), Carletti, Hartmann, and Ongena (2015), and Duso, Neven, and Röller (2007) study the stock market response to regulatory decisions or legislative actions. Contrary to prior work, which focuses on the role of outsiders – governments and regulators – in mergers, this paper studies the role of the political attitudes and partisanship across the acquirer and the target themselves.

Lastly, our paper is also related to prior research on the role of the cultural fit and of trust in mergers and acquisitions. To the extent that political similarity fosters trust, our paper is related to the studies by Guiso, Sapienza, and Zingales (2009) and Bottazzi, Da Rin, and Hellmann (2008), who demonstrate the importance of trust in cross-border financial investments by using macroeconomic and venture capital investment data, respectively. Further, several studies investigate the link between mergers and corporate culture. Ahern, Daminelli, and Fracassi (2015) find that the volume of cross-border mergers is smaller when countries are more culturally distant. Li, Mai, Shen, and Yan (2020) generate machine-learning-based measures of corporate culture and show that it plays an important role in merger incidence. Bereskin, Byun, Officer, and Oh (2018) show that similarity in firms' corporate social responsibility is positively correlated with the likelihood of a merger and with greater synergies, superior long-run operating performance, and fewer write-offs of goodwill. Lastly, based on survey evidence, Graham, Grennan, Harvey, and Rajgopal (2022) find that 46% of executives would walk away from a culturally misaligned target. Our estimates show that partisanship and political polarization play an increasingly important role in mergers and acquisitions, which is distinct from the role of corporate culture.

2. Data and Variables

To measure employees' political attitudes, we obtain information on individual contributions to political campaigns. The Federal Election Commission (FEC) maintains transaction-level records of individual donations organized by election cycle. Donations must be above a minimum value to be recorded in the file, and the minimum has changed over time: \$500 and above from 1975 to 1988, \$200 and above from 1989 to 2014, and above \$200 from 2015 onwards.[4]

For each transaction, the FEC records the transaction amount, date, ID of the committee receiving the donation, as well as information about the donor. The donor information includes, among other details, self-reported information on the name of the donor, state, zip-code, and city where the donor resides, and the donor's employer name. We utilize the self-reported employer names to match individuals with firms.

We match each FEC employer name with its closest CRSP name using bigram scores. We delete all matches with a bigram score less than 0.75, and manually check all matches with a score of 0.75 or higher. This yields 78,000 string matches that we manually check. Ultimately, we match 14.1 million donations out of 214 million donations with non-missing employer names from 1979 to 2021. The low match rate is explained by two observations. First, we only attempt to match employees with publicly traded firms. Consequently, employees of small businesses, non-profit organizations, and the public sector will not be matched. Second, we do not match donations from individuals who are not employed or self-employed. For example, there are 104 million donations reporting one of the following employer strings: "Not Employed", "Retired", "None", "Self", and "Self Employed." More details on the matching process are available in Appendix B.

Next, we classify donations into Republican or Democratic based on the affiliated party declared by the committee receiving the donation. Individuals are not allowed to make contributions directly to politicians; instead, they donate to Political Action Committees (PACs) that, in turn, expend money on political campaigns.

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[4] More information is available on the FEC's website: https://www.fec.gov/campaign-finance-data/contributions-individuals-file-description/.

PACs registered with the FEC, however, often do not declare a party affiliation. In fact, only 52% of PAC-election cycle observations correspond to PACs that declare a party affiliation.[5] To overcome this issue and retain as many observations as possible, we first identify PACs with no declared party affiliation that are connected to a specific candidate who does declare a party affiliation. We assign these PACs the party affiliation of their connected candidate. This procedure populates an additional 12% of the PAC-election cycle observations in our sample with party affiliations.[6] We then classify the remaining PACs based on their donations. Specifically, we assign a Democratic (Republican) affiliation to committees in a given election cycle when at least 80% of their donations go to committees declared Democratic (Republican). This procedure populates an additional 7% of the PAC-election cycle observations with party affiliations.[7]

The final sample comprises 4,310,589 donations corresponding to 9,253 unique firms, which an average donation of $9,301 in donations per firm each year, of which $5,034 is contributed to Democrats and $4,268 to Republicans. Fig. 1 shows the natural log of the aggregate number of donations to each party by year. It suggests that the number of donations has been increasing over time and that there is time-variation in the aggregate number of employee donations to the Democratic and Republican parties.

[5] An election cycle corresponds to the two-year House of Representatives election cycle. The FEC reports connected candidates for PACs every two years, and we use the same time frame to assign party affiliations.
[6] For example, in 2016, the committee "Secure Our Senate 2016" declared no party affiliation and was connected to Kamala Harris. We thus assign a party affiliation of "Democratic" to "Secure Our Senate 2016". From 2016 to 2018, 95% of the committee's donations went to committees declared Democratic, 5% went to committees with no declared party affiliation, and 0% went to committees declared Republican.
[7] To validate our method, we compare the donations of committees with declared party affiliations to donations of committees whose party affiliations we assigned. We find that our affiliation assignments are more highly correlated with partisan political donations than those of declared party affiliations.

Using these data, we construct a *Democratic Affiliation* score for each firm-year, defined as the fraction of donations to Democrats out of the total number of donations in the past 8 years.[8] By purging the estimates 8 years back, we generate estimates that are largely free from concerns that the most recent contributions are endogenously related to firms' merger decisions or outcomes through channels different from political partisanship. We ignore donations further in the past because they are less likely to reflect the current political affiliation of the firm's employees.

In our sample, the average number of donations used to calculate *Democratic Affiliation* is 263 for acquirers and 55 for targets. To address concerns about potential data scarcity, we provide estimates from robustness tests that use an alternative *Democratic Affiliation* score based on all the individual donations originating from the zip-code where the firm is headquartered. To construct the zip-code political measures, we obtain historical headquarter zip-code data from 10Ks/Qs (and all variants) filed on the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR), and then match each firm with donations originating from its headquarter zip-code using information reported to the FEC.[9] Since EDGAR started in 1995, this alternative measure is available from 1995 to 2021. The average number of donations using the zip-code political measure is considerably higher: 597 for acquirers and 690 for targets.

Fig. 2 assigns a *Democratic Affiliation* score to each state-decade based on our sample. The figure maps the proportion of donations made to Democratic committees in each state relative to total donations to Democratic and Republican committees over the past four decades. The resulting maps summarize the evolution of the geographical landscape of employee political contributions over the past 40 years. Most notably, West Coast- and New York-based firms increasingly lean towards the Democrats, whereas in most other states, firms lean more towards the Republicans.

[8] We construct similar measures based on the dollar value of donations instead of the number of donations and obtain virtually identical results. We therefore only report those based on the number of donations throughout the paper.
[9] We thank Bill McDonald for making the 10K/Q header data available online (https://sraf.nd.edu/).

To construct the sample of mergers, we obtain information on all U.S. domestic mergers announced between 1985 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms. We match the acquirer and target of each deal with the political contributions data and end up with 2,325 deals in which *Democratic Affiliation* is available for both the acquirer and the target. In a final step, we match the acquirers and the targets with information from the Center of Research in Security Prices (CRSP) and Compustat databases on firms' stock returns and accounting data.

Table 1 presents summary statistics for the acquirers (Panel A), targets (Panel B), and deals (Panel C) used in the analyses. Appendix A provides all variable definitions. Panels A and B show that the average acquirer is larger and has higher *Return on Assets* and *Return on Equity* compared to the average target. The average acquirer and average target have similar estimates of *Book-to-Market*, *Sales Growth*, *Book Leverage,* and *Cash Ratio*. Based on the measure of *Democratic Affiliation*, both acquirers and targets lean slightly more towards the Republican party.

Panel C of Table 1 presents summary statistics for the announced mergers included in the sample. The sample includes 2,325 announced deals, of which 16.3% are withdrawn, 12.4% are hostile, and 57.1% occur between parties that share the same 2-digit SIC code. The average distance between the headquarters of acquirers and targets is 832 miles. The average deal value is $3.9 billion. The main variable of interest, *Political Distance,* is the absolute value of the difference between the acquirer's and target's *Democratic Affiliation,* based on the number of donations. The average *Political Distance* for deals in the sample equals 0.325.

3. The Likelihood of Mergers

In this section, we investigate the effect of the political distance between firms on the likelihood of merger announcements. We conjecture that politically distant firms will be less likely to announce mergers for two main reasons. First, differences in political attitudes might negatively affect the success of merger negotiations. Second, such differences could adversely affect the prospects of post-merger integration, synergies, and outcomes. These conjectures are founded in extensive research showing that party affiliation is an important form of social identity (e.g., Huddy, Mason, and Aarøe (2015); Iyengar, Sood, and Lelkes (2012)), which inculcates hostility towards members of the outgroup.

We begin the analyses with descriptive evidence. Fig. 3 provides illustrative evidence on firms' political affiliations for the 50 largest mergers in our sample by transaction value. Each point corresponds to one of the 50 mergers and reflects the combination of the acquirer's and target's *Democratic Affiliation*. The main finding in Fig. 3 is the apparent clustering around the 45-degree line, suggesting mergers are more common between politically close firms.

In Table 2, we present the frequency distribution of merger announcements by political distance and presidential election cycle. The estimates in Table 2 suggest that the number of mergers declines as political distance increases. To test whether the pattern differs from a hypothetical distribution with randomized pairing between firms, we form all hypothetical merger pairs within a given presidential election cycle using the population of Compustat firms for which we have measures of political attitudes. Then, we utilize a χ^2 goodness-of-fit test between the realized and hypothetical distributions. At the 95% confidence level, we reject the null hypothesis that the number of mergers is random with respect to political distance in 7 out of the 10 presidential election cycles, and in all of the cycles since 2001. This test provides initial suggestive evidence that differences in political attitudes negatively affect the likelihood of merger announcements, particularly in more recent years when political polarization has been increasing in the U.S.

Next, we provide estimates from selection models of firms becoming acquirers or targets that follow the method used by Bena and Li (2014). For each merger announcement, we match acquirers and targets with several pseudo-targets and pseudo-acquirers in the year preceding the merger announcement. In the resulting sample, we create an indicator variable equal to one for the actual merger and zero for the pseudo-mergers.

We use three different control samples of potential acquirers and targets, all of which exclude firms that have been acquirers or targets in the three years preceding the merger as well as firms with missing measurements of political attitudes. First, we form a random control sample that matches each acquirer/target of a deal announced in year t with five paired firms drawn randomly from Compustat/CRSP in year t-1. This pool of potential merger participants captures merger clustering in time (Mitchell and Mulherin (1996), Maksimovic, Phillips, and Yang (2013)).

Second, we form an industry- and size-matched control sample that matches each acquirer/target of a deal announced in year t with up to five paired firms by industry—where industry definitions are based on 2-digit SIC codes—and by size from Compustat/CRSP in year t-1. This pool of potential merger participants captures merger clustering both in time and industry (Andrade, Mitchell, and Stafford (2001), Harford (2005)).

Third, we form an industry, size, and book-to-market matched control sample that matches each acquirer/target of a deal announced in year t with up to five paired firms—first matched by industry and then matched on propensity scores estimated using size and book-to-market ratios—from Compustat/CRSP in year t-1. We add the book-to-market ratio to the matching characteristics because prior studies show that it captures important drivers of mergers, such as growth opportunities (Andrade, Mitchell, and Stafford (2001)), overvaluation (Shleifer and Vishny

(2003), Rhodes-Kropf and Viswanathan (2004)), and asset complementarity (Rhodes-Kropf and Robinson (2008)).

In Table 3, we present coefficient estimates from conditional logit models predicting mergers. Panels A, B, and C correspond to the randomly-matched sample; the industry- and size-matched sample; and the industry-, size-, and book-to-market matched sample, respectively. In Panel D, we instead measure political distance using donations originating from the zip-code where the firm is headquartered. The regressions in each panel alternate with respect to the inclusion of control variables, Industry-by-Year fixed effects, and Deal fixed effects (each deal participant has one actual deal partner and up to 5 pseudo deal partners from the matched pairings).

The last column of each panel excludes hostile offers to focus on the announcement of negotiated deals. While political distance likely decreases the odds of announcing negotiated deals because it adversely affects the success of merger negotiations and post-merger integration, it might increase the odds of announcing hostile deals, which are noncooperative and result from disagreement by definition. Hence, we expect the negative effect of political distance to strengthen in the subset of negotiated deals.

Across all 16 regression specifications in Panels A, B, C and D of Table 3, the coefficient on the main variable of interest, *Political Distance*, is negative and statistically significant at the 1% level (except for one case where it is significant at the 5% level). These findings hold robustly across the three different control samples and after including all the control variables, Industry-by-Year fixed effects, or Deal fixed effects. They also hold when we measure firms' political attitudes based on donations originating from the zip-code where the firm is headquartered.

The economic magnitude of the effect of political distance on the likelihood of merger announcements is nontrivial. We estimate the marginal effect of political distance using linear probability models since the inclusion of fixed effects can confound the interpretation of marginal effects in conditional logit models. Based on these linear probability models, a one standard deviation increase in *Political Distance* reduces the likelihood of mergers by 0.59 to 1.34 percentage points, which implies a reduction of 6.4% to 14.6% relative to the sample-mean pseudo-likelihood of 9.18%.

Furthermore, we find that the coefficient estimate on *Political Distance* is 10-22% larger in magnitude when we exclude hostile bids and only focus on announced merger agreements. This finding holds across all three matched samples in Panels A, B, and C, and is consistent with our conjecture that hostile bids result from disagreements between acquirers and targets that are likely exacerbated by difference in political attitudes. We will formally test the prediction that the likelihood of deal hostility increases with political distance in Table 8 and restrict our attention in the remaining tests of merger formation to the subsample of merger agreements that exclude hostile bids.

Taken together, these findings suggest that political similarity across firms positively predicts merger announcements. Stated differently, the evidence suggests that greater political distance between firms decreases the likelihood that the two firms will choose to merge. In the next set of analyses, we compare between the effects of differences in political attitudes and differences in other dimensions of corporate culture across firms.

4. Corporate Culture

Existing studies have shown that corporate culture plays an important role in merger formation and merger success (e.g., Ahern et al. (2015); Bereskin et al. (2018)). Are the political leanings of rank-and-file employees another proxy for corporate culture or does political distance affect merger likelihood beyond the effects of cultural distance? In this section, we use measures of firm culture from Li, Mai, Shen, and Yan (2020) to empirically study the distinction between politics and culture.

The five measures of corporate culture from Li, Mai, Shen, and Yan (2020) are *Innovation*, *Integrity*, *Quality*, *Respect*, and *Teamwork*. Those measures are constructed from the question-and-answer section of earnings call transcripts using a machine learning technique – the word embedding model. The data are available from 2002 to 2018 for the subset of firm-years that have electronically available transcripts. We start by examining the correlations between our political affiliation measure, *Democratic Affiliation*, and each of the five measures of culture. The correlation estimates are: 0.21 with *Innovation*, 0.06 with *Integrity*, 0.11 with *Quality,* 0.07 with *Respect,* and 0.17 with *Teamwork*. These correlations suggest that political party affiliation is distinct from measures of corporate culture.

Next, we calculate *Cultural Distance* separately for each measure as the absolute value of the difference between the acquirer's and target's value for that measure. We also calculate an overall measure of cultural distance, *Aggregate Cultural Distance,* which is the sum of all five cultural distance measures. To facilitate a meaningful comparison, we standardize the *Political Distance* and *Cultural Distance* measures by subtracting their respective sample means and dividing by their respective sample standard deviations. The correlation estimates between *Political Distance* and each of the five *Cultural Distance* measures are: 0.00 with *Innovation Distance*, -0.02 with *Integrity Distance*, 0.03 with *Quality Distance*, -0.01 with *Respect Distance*, -0.01 with *Teamwork Distance*, and 0.00 with *Aggregate Distance*. These correlations suggest that political differences are distinct from cultural differences, and quell concerns about collinearity.

Next, we include the *Cultural Distance* between the target and the acquirer alongside the *Political Distance* between them in the tests of merger formation likelihood. We note that the sample size of our tests is significantly reduced compared to our baseline specification in Table 3 because the corporate culture data is available only for a subset of firm-years. To mitigate this issue, we linearly interpolate years where corporate culture measures are missing and we linearly extrapolate the sample period to 2021.[10]

Panel A of Table 4 reports coefficient estimates of conditional logit regressions predicting merger formation using the industry, size, and book-to-market matched sample with each *Cultural Distance* measure added individually. The coefficient estimates on *Political Distance* remain negative and statistically significant at the 5% level across all the specifications. The coefficient estimates vary from -0.129 to -0.130 across the specifications, suggesting that they are effectively unchanged (compared to the baseline specification in Table 3) after controlling for various dimensions of *Cultural Distance*. Moreover, the coefficient estimates on the measures of *Cultural Distance* are negative in four out of the five specifications, consistent with the prior findings that culturally distant firms are less likely to merge.

In Panel B of Table 4, we consider the *Aggregate Cultural Distance* (Column 2) as well as all the individual *Cultural Distance* measures simultaneously (Column 3). As before, the coefficient estimate on *Political Distance* is negative and statistically significant at the 5% level across all columns. The coefficient estimates on *Aggregate Cultural Distance* and the individual corporate *Culture Distance* measures are negative (with the exception of *Teamwork*).

Overall, the results in this section provide evidence that political dissimilarities affect merger formation above and beyond the impact of cultural dissimilarities. The findings draw a distinction between cultural dissimilarity and political dissimilarity, consistent with past research showing that social norms temper disapproval of culturally dissimilar groups but not politically

[10] Specifically, we interpolate and extrapolate culture measures for firms with at least three data points throughout the sample period. If a firm has less than three data-points, we carryforward values to populate the data. Note, however, that we obtain similar results if we do not interpolate/extrapolate the sample.

dissimilar ones (e.g., Himmelfarb and Lickteig (1982); Iyengar and Westwood (2015); Maccoby and Maccoby (1954); Sigall and Page (1971)).

The next set of analyses test whether changes in national political polarization and economic conditions impact the relation between political distance and the likelihood of mergers. We conjecture that political disapproval is likely increasing in the level of national political polarization and decreasing during economic recessions when solidarity and bipartisanship tend to dominate the national political narrative.

5. Political Polarization and Economic Conditions

We open this section by testing whether political polarization influences the relation between political attitudes and the likelihood of mergers. Since political distance plays an important role in merger announcements, we conjecture that when the U.S. is more politically polarized, the political distance between the acquirer and the target will have a stronger negative effect on the probability of mergers. This hypothesis is consistent with prior research, which shows that political polarization exacerbates the impact of partisanship on behavior (e.g., Iyengar and Westwood (2015); McConnell, Margalit, Malhotra, and Levendusky (2018)), and with the recent findings of Fos, Kempf, Tsoutsoura (2022), who find that executive teams in U.S. firms have also become more partisan in recent years.

We use two variables to study political polarization. The first variable is based on the Partisan Conflict Index constructed by Azzimonti (2018). The Partisan Conflict Index is computed monthly and measures the frequency of newspaper articles reporting political disagreement about government policy, scaled by the total number of news articles in the same newspapers over the same month. We calculate the annual average of the Partisan Conflict Index to generate the variable *PCI*.

We construct the second variable, the House Partisanship Index (*HPI*), using outcomes on yea-or-nay voting in the United States House of Representatives. For each vote in the House of Representatives, we define Partisan Disagreement as follows:

$$Partisan\ Disagreement_{v,t} = |RepYes_{v,t} - DemYes_{v,t}| \tag{1}$$

where $RepYes_{v,t}$ is the proportion of "yea" votes cast by Republican representatives as a proportion of all Republican votes cast on vote v in year t, and $DemYes_{v,t}$ is the proportion of "yea" votes cast by Democratic representatives as a proportion of all Democratic votes. We exclude all independent votes, absent votes, and abstain votes. The variable *Partisan Disagreement* increases (decreases) when political parties cast votes in the opposite (same) direction. Then, we define *HPI* as the average *Partisan Disagreement* for all votes in the U.S. House of Representatives in a given calendar year.

We standardize both variables by subtracting their respective sample means and dividing by their respective standard deviations, and plot their values in Fig. 4. In general, values for both measures of political polarization are greater in the second half of the sample. This pattern is consistent with numerous studies in political science showing that polarization and hostility across party lines have increased in the U.S. in more recent years (e.g., McCarty, Poole, and Rosenthal (2006); Haidt and Hetherington (2012); Iyengar, Sood, and Lelkes (2012); Lott and Hassett (2014); Iyengar and Westwood (2015); Gentzkow (2016); Boxell, Gentzkow, and Shapiro (2017); Autor, Dorn, Hanson, and Majlesi (2020)). We also note that political polarization appears lower during NBER recessions. We will revisit this issue when we study the effects of economic conditions.

To investigate the influence of political polarization on merger formation, we separately estimate the effects of political distance between the acquirer and the target from 1995 to 2021 in subsamples of low vs. high political polarization. We divide the sample around two indicator variables, *High PCI* and *High HPI*, which are equal to one when the values of *PCI* and *HPI*, respectively, are above median, and zero otherwise.

Table 5 reports the coefficient estimates from tests using the most stringent, industry, size, and book-to-market, matched samples. In columns (1) and (2), we separately estimate the effect of political distance when *High PCI* is equal to zero and one, respectively. The coefficient estimate on *Political Distance* in column (2), where polarization is higher, is nearly triple the value of the estimate in column (1), where polarization is lower, and the difference between the coefficients is statistically significant at the 10% level (*t*-statistic = 1.78). In columns (3) and (4), we repeat the analysis measuring political polarization using *HPI* and obtain a similar result. The coefficient estimate on *Political Distance* in column (4), where polarization is higher, is nearly quadruple the value of the estimate in column (3), where polarization is lower, and the difference between the coefficients is statistically significant at the 5% level (*t*-statistic = 2.07).

Overall, these results show that there are significant differences in the relevance of political similarity to merger formation between periods of lower and higher political polarization. The covariation of the effect's magnitude with political polarization is intuitive and supports our interpretation that the results reflect the effects of political attitudes rather than a correlated omitted variable unrelated to firms' political attitudes.

We now turn to the role of economic conditions and study the effect of recessions on the relation between political attitudes and mergers and acquisitions. We conjecture that economic recessions attenuate the negative impact of political distance on the likelihood of merger formation for two reasons. First, as shown in Fig. 4, political polarization is lower during recessions (NBER recessions are represented by shaded areas). This finding might be driven by the tendency of Democrats and Republicans to cooperate more during economic downturns – for example, the *HPI* suggests that House representatives are more likely to vote together during recessions despite party differences – and is consistent with prior evidence (e.g., Stanig (2013)). Second, during recessions, firms' incentives for entering a merger agreement can change. In particular, mergers during recessions might be necessity mergers that allow the merging firms to restructure, downsize, and continue to operate (e.g., Dutz (1989), Jensen (1993), Mitchell and Mulherin (1996)). As such, firms might put aside their political and ideological differences.

To test the role of recessions in the relation between political distance and the likelihood of merger formation, we create an indicator variable, *Recession*, equal to one for mergers announced during NBER recessions and zero otherwise. Table 6 reports coefficient estimates of conditional logit regressions testing the effects of political distance on merger formation. In column (1), which corresponds to non-recessionary periods, the coefficient estimate on *Political Distance* is negative and statistically significant at the 1% level. In contrast, the estimate for recessionary periods in column (2) is positive and not statistically significant. The difference between the coefficients in columns (1) and (2) is economically large but not statistically significant (difference = 0.585; *t*-statistic = 1.25). Overall, this result indicates that recessions moderate the role of political differences in merger formation.

6. Mechanisms

In this section, we seek to provide evidence on the mechanisms through which political attitudes affect merger formation. We first provide evidence on post-merger integration using textual analysis of firms' financial reports. We then provide evidence on merger negotiations by studying the likelihood of merger completion and hostile takeovers. These channels are also illustrated through anecdotal evidence provided in Appendix C.

6.1 Integration

In this subsection, we explore post-merger integration as a channel through which political attitudes can influence merger formation. We conjecture that the political distance between acquirers and targets will be more important for merger formation when the acquirer and target are integrating their businesses.

We measure the importance of integration for each announced deal by searching for keywords in the acquirer's Securities and Exchange Commission (SEC) filings following merger announcement. Specifically, we read the closest form 10K/Q filed post-announcement, and the closest form DEF 14A filed within a year after announcement, and count the number of times the words "integrate" or "integration" appear in the documents.[11,12] We set the variable *Integration* equal to zero for deals in which integration is mentioned less frequently than the median frequency, and equal to one when integration is mentioned more frequently than the median.

In Table 7, we separately estimate the effects of political distance on the likelihood of merger formation in subsamples formed based on whether integration is mentioned in SEC filings more or less frequently than the median. As before, we only present coefficient estimates of conditional logit regressions using the industry, size, and book-to-market matched samples. Column (1) corresponds to the subsample where acquirers in the realized deals mention integration in their SEC filings less frequently than the median acquirer (i.e., *Integration* = 0). The coefficient estimate on *Political Distance* is negative but not statistically significant. In column (2), we repeat

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[11] A representative example where mentioning these terms is informative about the cost of integration is the acquisition of Asterias Biotherapeutics Inc by BioTime Inc. BioTime's 10-Q following the acquisition states: "If the merger is completed, BioTime expects to incur significant costs in connection with consummating the merger and integrating the operations of Asterias. BioTime may incur additional costs to maintain employee morale and to retain key employees."

[12] We exclude the acquisition of Rotech Medical Corp by Integrated Health Services Inc because the word "integrate" is mentioned 352 times in the acquirer's 10Q following announcement. We also exclude deals where "Maxim Integrated Products Inc" is the acquirer.

the test where the acquiring firms' SEC filings include above median references to integration. The coefficient estimate on *Political Distance* is negative and statistically significant at the 1% level, indicating that greater political differences negatively influence the formation of deals where the merging firms plan to combine operations. While the difference between the two coefficients (-0.650) is not statistically significant at conventional levels, the coefficient estimate in column (2) is more than twice as large as the coefficient estimate in column (1).

Altogether, the results in Table 7 suggest that post-merger integration is an important channel through which differences in political ideology affect merger formation.

6.2 Negotiations and Deal Hostility

Another channel through which the effects of political differences can materialize is in the tone of negotiations between acquirers and targets. Negotiations between the acquirer and target could collapse before announcement, possibly leading the acquirer to initiate a hostile takeover bid. As Schwert (2002) points out, a hostile takeover is simply the announcement of an unnegotiated offer. We hypothesize that greater political distance increases the chance of a breakdown in negotiations preceding the merger announcement, resulting in a greater chance of a hostile bid.

Furthermore, after the merger announcement, managers at either firm will learn more about their merger partner as integration discussions continue. Similarity in political attitudes can play a role in successfully reaching an agreement on integration issues and completing the merger. We therefore hypothesize that announced mergers between more politically distant firms will have a lower likelihood of completion.

These hypotheses are motivated by ample evidence that political differences are barriers to cooperation. For example, McConnell, Margalit, Malhotra, and Levendusky (2018) show experimentally that partisanship hurts cooperation in everyday economic behavior of workers and consumers. Iyengar and Westwood (2015) show that political polarization exerts powerful effects on nonpolitical judgments and behaviors and leads to confrontation rather than cooperation.

To test these hypotheses, we focus on the sample of announced deals, and create two outcome variables, *Hostile* and *Withdrawn*. The variable *Hostile* is an indicator variable equal to one if there is a hostile or unsolicited bid, and zero otherwise. The variable *Withdrawn* is an indicator variable equal to one if a deal is withdrawn after its announcement and zero otherwise. We then estimate conditional logit regressions explaining these two variables.

We present the coefficient estimates of these tests in Table 8. In columns (1) and (2), the outcome variable is *Hostile*, and the coefficient estimate on *Political Distance* is positive and statistically significant at the 5% level. The coefficient estimates imply that, conditional on announcement, a one standard deviation increase in political distance is associated with a 1.25-1.77 percentage point increase in the likelihood of a hostile bid, representing a 10.2-14.3% increase compared to the sample mean of 12.4%.

In columns (3) and (4) of Table 8, we test how political distance influences post-announcement negotiations leading to merger withdrawal. The coefficient estimate on *Political Distance* is positive and statistically significant at the 5% level and 10% level in columns (3) and (4), respectively. The coefficient estimates imply that a one standard deviation increase in political distance between the target and acquirer is associated with a 2.03-2.33 percentage point higher probability that the merger will fail to complete. Relative to the sample mean withdrawal rate of 16.3%, this represents a 12.4-14.3% increase in failure to complete.

Overall, the results in this subsection show that not only does political distance influence the likelihood of deal announcement, it also affects the hostility of the deal and the likelihood of its completion.

7. Merger Announcement Returns and Post-Merger Performance

In the last set of analyses, we investigate the effects of political distance on announcement returns and post-merger performance. We propose that more politically distant acquirers and targets would experience more difficulties in post-merger integration, leading to lower merger value and performance.

We begin by considering the effects of political distance on combined merger announcement returns. Table 9 presents estimates from ordinary least squares regressions explaining cumulative combined abnormal returns. In Panel A, abnormal returns are those in excess of the market return. In Panels B and C, abnormal returns are the excess returns from the CAPM (Sharpe (1964); Lintner (1965)) and the Fama and French (1993) 3-Factor plus Momentum (Carhart (1997)) Model (FF3M), respectively. Columns (1) and (2) of each panel correspond to the use of a three-day window (-1,1), and columns (3) and (4) correspond to a six-day window (-1, 5).

In all the regression specifications, the coefficient estimates indicate that the political distance between the acquirer and the target has a negative effect on merger announcement returns. In all models of Panel A, the estimates are statistically significant at conventional levels. In Panels B and C, the coefficient estimate on Political Distance is statistically significant across six of the eight specifications. Furthermore, the coefficient estimates suggest that the effects are economically meaningful across all regression specifications. We estimate that a one standard deviation increase in *Political Distance* corresponds to a decrease in announcement returns between 34.8 to 42.9 basis points. Collectively, the results in Table 9 suggest that political differences between firms are negatively associated with merger announcement returns.

We also investigate whether political distance affects post-merger performance. To this end, we employ two measures of the combined firm's performance for the three years following the merger: (1) industry-adjusted return on assets (*3-year Industry-adjusted ROA*); and (2) buy-and-hold abnormal returns (*3-year BHAR*) using the Capital Asset Pricing Model (CAPM).

We present coefficient estimates from OLS regressions explaining post-merger performance in Table 10. In columns (1) and (2), the dependent variable is *3-year Industry-adjusted ROA*. The coefficient estimate on *Political Distance* is negative and statistically significant at the 5% level in both columns. An increase of one standard deviation in *Political Distance* is associated with a decrease of 0.56-0.67% in average annual *ROA*. In columns (3) and (4), the outcome variables are three-year BHARs using the CAPM. In both columns, the coefficient estimate for *Political Distance* is negative and statistically significant at conventional levels. The estimates imply that an increase of one standard deviation in *Political Distance* corresponds to a decline of 9.5-12.8% in 3-year CAPM buy-and-hold abnormal returns.

Overall, the findings in this section indicate that political divergence between the acquirer and the target is an obstacle to post-merger integration, with negative consequences for post-merger performance and value. An important caveat, however, is that these estimates likely underestimate the true effect of political partisanship on performance because, as we have shown, politically misaligned firms are less likely to merge in the first place.

8. Conclusion

This paper provides novel evidence that differences in political attitudes between firms play an important role in merger decisions and outcomes. We proxy for corporate political attitudes using detailed data on employees' individual political contributions to the campaigns of the two primary political parties in the U.S over the prior 8 years. By purging these measures 8 years back, well before a merger was contemplated, and by focusing on the personal contributions of a firm's entire labor force, which is dominated by rank-and-file employees who are uninvolved in merger decisions, we generate estimates that are largely free from concerns that political contributions are endogenously related to firms' merger decisions or outcomes through channels different from political partisanship.

The estimates show that firms are more likely to announce and complete mergers when they have similar political attitudes. These effects are distinct from those of other dimensions of corporate culture. Moreover, the level of national political polarization acts as a moderator — the role of political partisanship is more pronounced when political polarization is greater. Macroeconomic conditions are another moderator — the impact of political differences is weaker during economic recessions, when polarization is lower and firms merge to restructure, downsize, and continue operating. We also find that political differences are more pronounced when the acquirer and the target seek to integrate their business operations. Finally, merger announcement returns and post-merger performance are stronger for more politically similar companies.

Collectively, the findings presented in this paper suggest that political attitudes and polarization affect the allocation of real assets in the economy. As such, this paper contributes to the vast literature studying the causes and consequences of mergers and acquisitions by showing that political similarity is a strong predictor of merger formation and merger success, and that the effects of political similarity vary over time with variations in the level of political polarization and in macroeconomic conditions.

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Appendix A: Variable Definitions

Variable	Definition
Firm-Level Political Measures	
Democratic Affiliation	The fraction of the number of donations to Democrats over the total number of donations to both Democrats and Republicans in the past 8 years.
Democratic Affiliation (V)	The fraction of the value of donations to Democrats over the value of total donations to both Democrats and Republicans in the past 8 years.
HQ Democratic Affiliation	The fraction of the number of donations to Democrats over the total number of donations to both Democrats and Republicans in the past 8 years, calculated using all individual donations originating from the zip-code where the firm is headquartered.
Pair-Level Political Measures	
Political Distance	The absolute value of the difference between acquirer's and target's Democratic Affiliation.
Political Distance (V)	The absolute value of the difference between acquirer's and target's Democratic Affiliation (V).
HQ Political Distance	The absolute value of the difference between acquirer's and target's HQ Democratic Affiliation.
Polarization Measures	
PCI	The Partisan Conflict Index was constructed by Azzimonti (2018). It is computed monthly and measures the frequency of newspaper articles reporting political disagreement about government policy scaled by the total number of news articles in the same newspapers over the same month. The Partisan Conflict Index is normalized to average 100 in 1990. We take the annual average of the Partisan Conflict Index to generate the variable *PCI*.
HPI	The House Partisanship Index is constructed using outcomes on yea-or-nay voting in the United States House of Representatives. For each vote in the House of Representative, we define Partisan Disagreement as follows: $Partisan\ Disagreement_{v,t} = \lvert RepYes_{y,t} - DemYes_{y,t} \rvert$ where $RepYes_{v,t}$ is the proportion of "yea" votes cast by Republican representatives as a proportion of all Republican votes cast on vote v in year t. $DemYes_{v,t}$ is, in turn, the proportion of "yea" votes cast by Democratic representatives as a proportion of all Democratic votes. We exclude all independent votes, absent votes, and abstain votes. The variable *Partisan Disagreement* increases (decreases) when political parties cast votes in the opposite (same) direction. Then, we define *HPI* as the average *Partisan Disagreement* for all votes in the U.S. House of Representatives in calendar year t.

Financial Variables

Book Assets	Total Assets, the natural logarithm of total assets
Book to Market	Book equity divided by market equity. Market equity is the equity market capitalization defined as PRCC_C*SCHO, winsorized at the 1st and 99th percentiles.
Leverage	Book liabilities divided by book assets (LT/AT)
Cash Ratio	Cash and cash equivalents divided by book assets (CHE / AT)
ROA	Net income divided by total book assets (NI/AT)
Industry-adjusted ROA	ROA minus the median ROA from the sample of firms in the same 2-digit SIC code in the same year.
3-year Industry-adjusted ROA	The arithmetic average of Industry-adjusted ROA reported in the three fiscal years following merger completion.
Sales Growth	Percentage growth in sales

Deal-Level Variables

Deal Value	The proposed deal value at announcement, in $millions
PostDealOwnership	The proportion of the target firm the acquirer will own if the deal completes as stated on the announcement day
Relative Size	Acquirer book assets divided by target book assets, winsorized at the 1st and 99th percentiles.
HQ Distance	The distance, in hundreds of miles, between the zipcode of the acquiror's headquarters and the zipcode of the target's headquarters
Integration	Indicator variable equal to one for mergers where the DEF14A or post-merger 10K/Q filing mentions the words "integrate" or "integration" more frequently than the median deal and zero otherwise
Cash Only	Indicator variable equal to one if the consideration structure at announcement is all cash and zero otherwise.
Diversifying	Indicator variable equal to one if the acquiror and target are classified under different 2-digit Standard Industrial Classification (SIC) codes and zero otherwise
Hostile	Indicator variable equal to one if the announced bid is hostile or unsolicited and zero otherwise
Withdrawn	Indicator variable equal to one if the announced deal is withdrawn and zero otherwise

Appendix B: Matching FEC Data

The FEC does not maintain a standardized method to record employer names. For example, the telecommunications company Verizon appears as "Verizon Communications Inc" in the Center of Research in Security Prices (CRSP) names file. However, it is reported in approximately 500 different ways in the FEC files. Examples include: "Verizon", "Verizon Comm", "Verizon Communications", "Verizon Communications Inc", "Verizon Communications, Inc", etc. Therefore, we cannot use direct matching on names, and develop our own matching procedure to match employer strings in the FEC individual donation files to company historical names in CRSP.

We start from the FEC individual donations bulk data, available from 1979 to 2018. We drop any employer string that appears fewer than 5 times throughout the sample. We then apply a series of edits to standardize the data. The edits include dropping all symbols such as hyphens, underscores, and question marks. To minimize false matches, we overwrite common terms such as "communications", "development", "real estate", "enterprise", and "limited" with their respective abbreviations. These terms are common to many company names and can inflate the matching score, especially when the rest of the name is short. Finally, we replace numbers with their full spelling to increase the weight of numbers in the matching score. We apply the same set of edits to company historical names in CRSP.

After standardizing the data, we calculate the bigram score between each employer string in the FEC files and each company name available in the CRSP names files after 1978. Bigram score decomposes each string into elements of two characters on a moving-window basis, and then calculates a similarity score as follows:

$$similscore = \frac{number\ of\ common\ bigrams}{\sqrt{number\ of\ bigrams\ in\ string\ 1 * number\ of\ bigrams\ in\ string\ 2}}.$$

similscore thus ranges from 0 to 1. For example, consider the two strings: “Verizon Inc” and “Verzon Inc”. Bigram decomposes each string into elements of two characters as follows:

“Verizon Inc”: “Ve”, “er”, “ri”, “iz”, “zo”, “on”, “n ”, “ I”, “In”, “nc”

“Verzon Inc”: “Ve”, “er”, “rz”, “zo”, “on”, “n ”, “ I”, “In”, “nc”

Hence, the similarity score between the above two strings is:

$$similscore = \frac{8}{\sqrt{10 * 9}} = 0.84.$$

We keep the best matched CRSP name for each FEC employer string. We delete all matches with a bigram score less than 0.75, and manually check all matches with a score of 0.75 or higher.

Appendix C: Anecdotal evidence

Phycor Inc. and MedPartners Inc.

Political distance: 0.833 (91st percentile of announced deals in our sample)

[i]t became apparent that the differences [between] the two companies were significant," said Larry House, MedPartners' chairman and chief executive. In discussions over several months, he said, it became obvious that the firms' "business philosophies and practices" were incompatible. -- Los Angeles Times (January 8, 1998)

In 1998, two physician management companies, Phycor Inc. and MedPartners Inc. announced an $8 billion merger. The market reacted negatively to the merger announcement. The combined market-adjusted returns were only 0.18% on the announcement day and -5.80% over the subsequent five trading days. Phycor, the acquirer, had returns of -23% on the first day after the announcement. Ultimately, the two companies did not merge, citing differences in strategies and higher-than-expected costs of integration.

LSI Logic Corp and Agere Systems

Political distance: 0.772 (90th percentile of announced deals in our sample)

In addition, key employees may depart because of issues relating to the uncertainty and difficulty of integration or a desire not to remain with us following the proposed merger. The loss of services of any key personnel or the inability to hire new personnel with the requisite skills could restrict our ability to develop new products or enhance existing products in a timely matter, to sell products to customers or to manage our business effectively. -- LSI Logic Corp's post-announcement 10-K

In 2006, semiconductor and software designer LSI Logic Corp announced agreement to acquire rival and chipmaker Agere Systems. The market reacted negatively with the combined announcement returns being -0.0287. The acquisition was completed, however, LSI Logic Corp ended up discontinuing several development projects citing difficulties integrating Agere Systems and retaining key employees. The three-year buy and hold return of the deal is -0.0820

Figure 1
Employees' Individual Political Donations by Party and Year

This figure plots the natural logarithm of the annual number of employees' individual political donations to each party for the period 1979-2021. The sample includes all the individual political donations from the Federal Election Commission (FEC) database that could be matched to CRSP/Compustat firms.

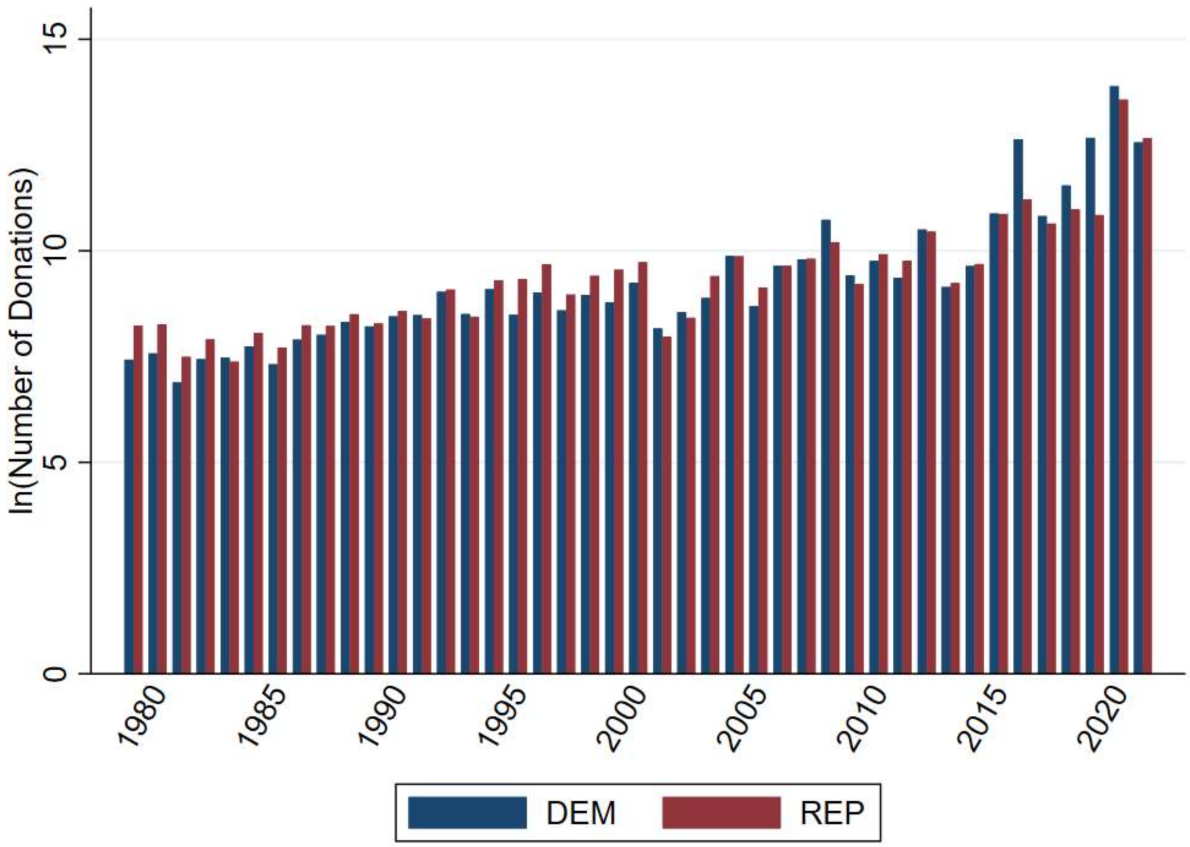

Figure 2
Political Donations by Decade and State

This figure maps the proportion of employees' individual political donations made to Democratic committees as a percentage of donations to both Democratic and Republican committees in each state. Each map represents a decade of donations. The sample includes all the individual political donations from the Federal Election Commission (FEC) database that could be matched to CRSP/Compustat firms.

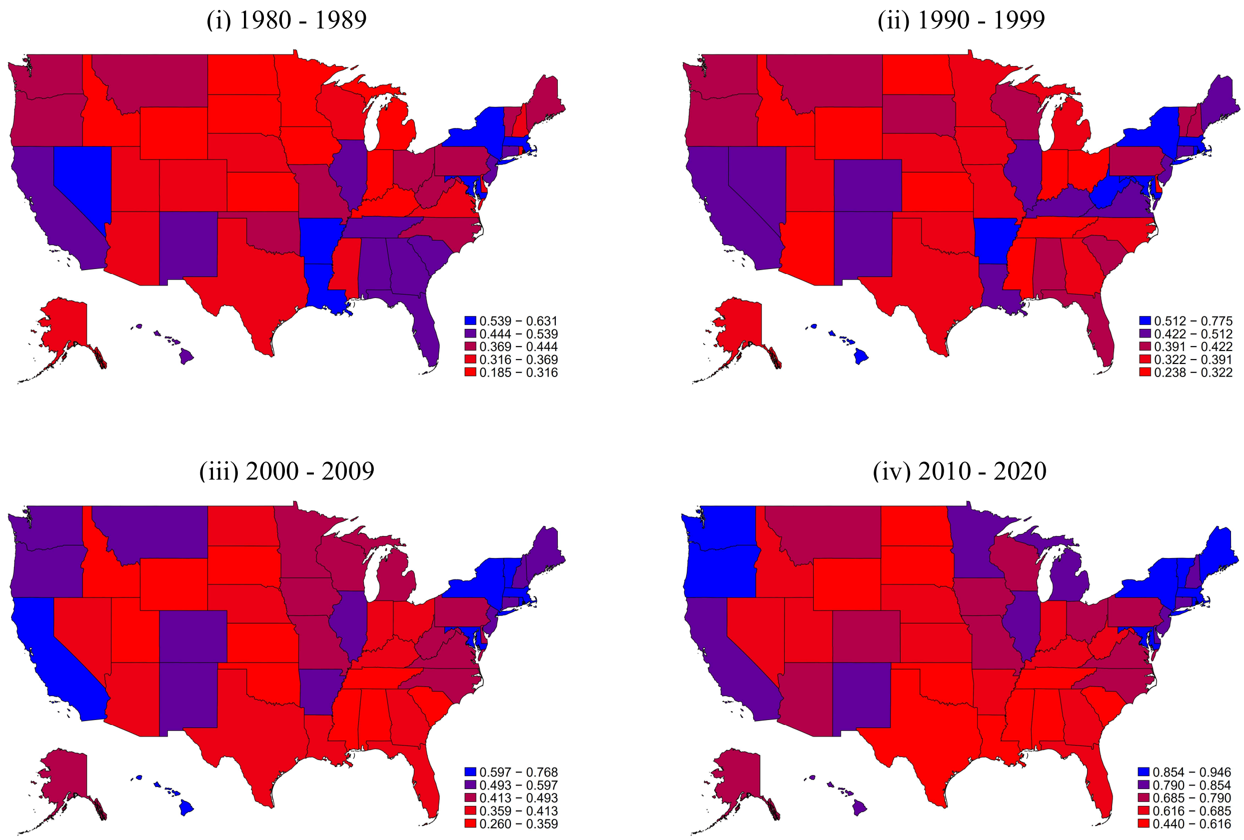

Figure 3
Deal Incidence by Acquirer and Target Party Affiliation

This figure plots acquirers' and targets' Democratic Affiliation for the 50 largest announced deals (by transaction value) in the sample. Democratic Affiliation is the number of employees' individual donations to Democrat committees divided by the number of donations to both Democrat and Republican committees. Additionally, we present a 45-degree line, representing where political distance is measured as zero (i.e. political similarity is maximized).

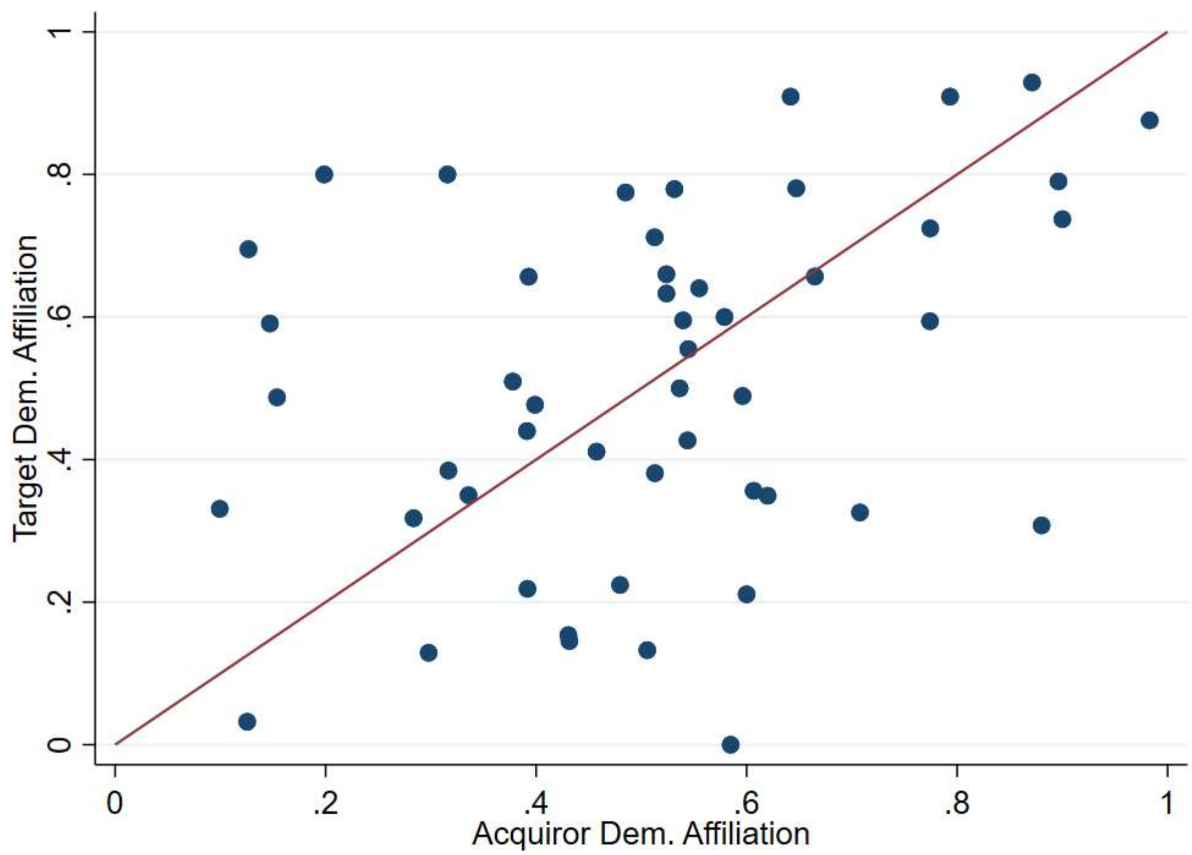

Figure 4
Political Polarization from 1995 - 2021

This figure plots Political Polarization from 1995 to 2021 using two measures that have been standardized by subtracting the sample mean and dividing by the sample standard deviation. The first is the standardized value of the annual average of the Partisan Conflict Index (*PCI*) from Azzimonti (2018). The second is the standardized value of the annual House Partisanship Index (*HPI*), which measures the tendency of U.S. House of Representatives members to vote on opposite sides along party lines. All variable definitions are given in Appendix A. Shaded areas are NBER recession periods.

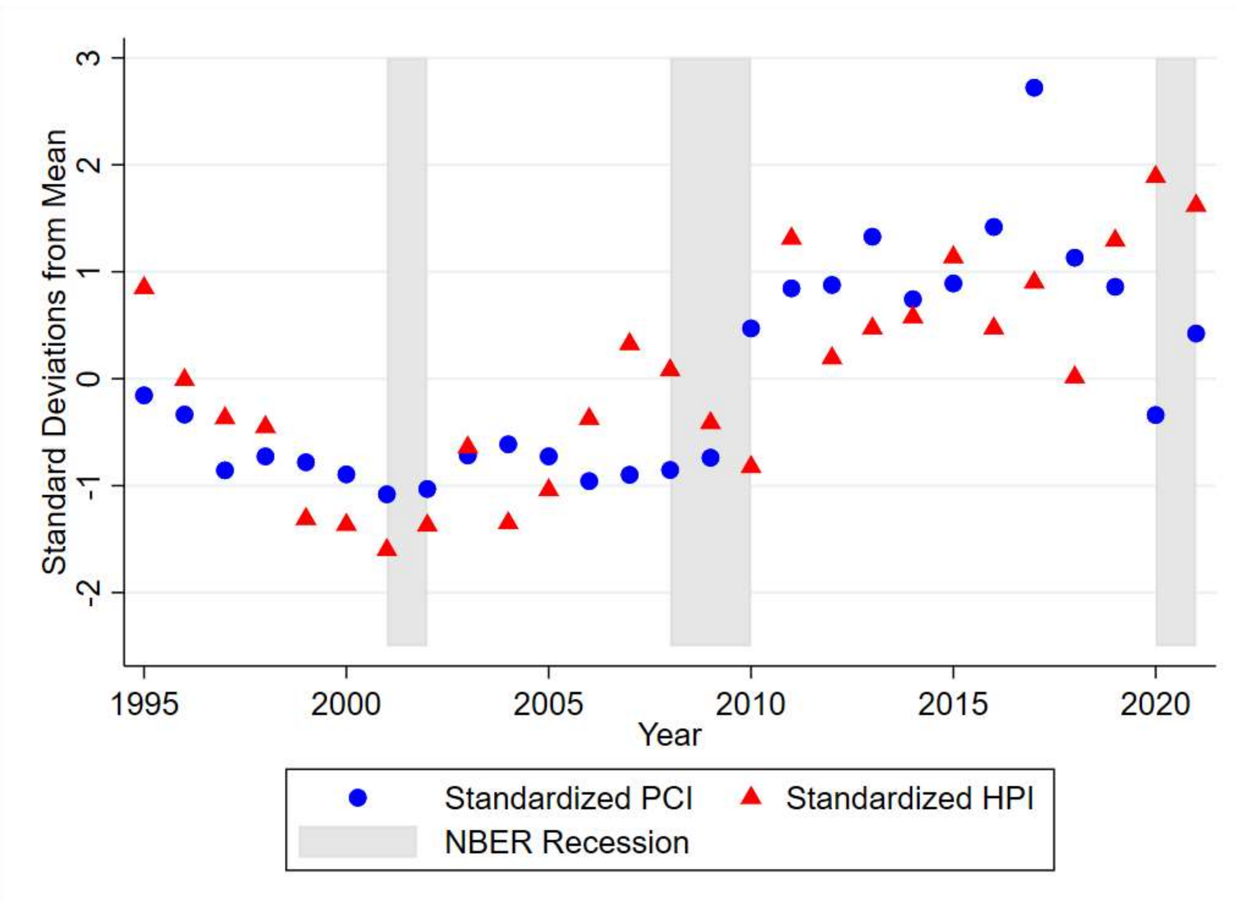

Table 1
Acquirer, Target, and Deal Descriptive Statistics

This table presents summary statistics for the acquirers and targets in the sample. Panel A describes acquirers and Panel B describes targets. Panel C describes the characteristics of announced deals. The sample includes 2,325 U.S. domestic mergers announced between 1985 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that political donation data be available for both the acquirer and the target. All variable definitions are given in Appendix A.

Panel A: Acquirer Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Democratic Affiliation	0.444	0.304	0.19	0.438	0.667	2325
Democratic Affiliation (V)	0.425	0.311	0.155	0.404	0.667	2325
Book Assets ($mil)	35606	123789	1736	6280	23179	2295
Book to Market	0.744	9.645	0.264	0.453	0.688	2295
Sales Growth	1.216	0.671	1.021	1.102	1.242	2256
Book Leverage	0.62	0.219	0.474	0.612	0.785	2295
Cash Ratio	0.126	0.16	0.023	0.065	0.159	2295
Return on Assets	0.041	0.169	0.012	0.039	0.076	2294
Return on Equity	0.094	2.73	0.073	0.127	0.188	2294

Panel B: Target Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Democratic Affiliation	0.444	0.36	0.083	0.417	0.769	2325
Democratic Affiliation (V)	0.429	0.367	0.058	0.367	0.778	2325
Book Assets ($mil)	9628	66979	301	1147	4089	2080
Book to Market	1.614	50.986	0.303	0.51	0.79	2080
Sales Growth	1.154	0.553	0.984	1.077	1.211	2011
Book Leverage	0.614	0.271	0.426	0.611	0.81	2080
Cash Ratio	0.15	0.194	0.022	0.066	0.194	2077
Return on Assets	-0.005	0.174	-0.004	0.022	0.059	2079
Return on Equity	0.013	1.993	-0.009	0.089	0.151	2079

Panel C: Announced Deal Summary Statistics

Variable	Mean	St.Dev	p25	Median	p75	N
Political Distance	0.325	0.268	0.109	0.258	0.5	2325
Political Distance (V)	0.344	0.277	0.112	0.278	0.518	2325
Deal Value ($mil)	3953	11083	215	817	2677	2325
PostDealOwnership	0.884	0.294	1	1	1	1910
Relative Size (Acq/Tar)	66.043	804.616	1.577	4.207	16.195	2055
HQ Distance (100s of miles)	8.323	8.199	1.662	5.897	12.793	2283
Cash Only	0.355	0.479	0	0	1	2325
Diversifying	0.429	0.495	0	0	1	2325
Hostile	0.124	0.33	0	0	0	2325
Withdrawn	0.163	0.369	0	0	0	2325

Table 2
The Frequency of Mergers by Political Distance and Election Cycles

This table shows the frequency of M&A deal announcements across ranges of political distance and U.S. Presidential election cycles. We present merger announcement counts by presidential election cycle, defined as the four years leading up to a U.S. Presidential Election. For each cycle, we present χ^2 tests against a hypothetical distribution of all possible firm combinations for which we have data in that cycle. The sample includes 2,325 U.S. domestic mergers announced between 1985 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that political donation data be available for both the acquirer and the target. All variable definitions are given in Appendix A.

Election	Political Distance							
Cycle	[0,0.2]	(0.2,0.4]	(0.4,0.6]	(0.6,0.8]	(0.8,1]	Total	χ^2	p-value
1988	68	24	27	15	17	151	7.27	0.05
1992	68	45	23	18	22	176	6.45	0.06
1996	87	61	44	33	21	246	0.90	0.14
2000	187	147	91	50	42	517	4.81	0.11
2004	116	54	46	27	21	264	9.70	0.02
2008	114	81	47	18	16	276	22.14	0.00
2012	92	51	30	15	14	202	17.55	0.00
2016	99	65	33	19	10	226	26.76	0.00
2020	87	52	40	15	9	203	21.01	0.00
2021*	31	17	9	5	2	64	7.34	0.05
Total	949	597	390	215	174	2325	57.29	0.00

*The 2024 election cycle only contains one year in the data.

Table 3
The Likelihood of Merger Formation

This table presents estimates from conditional logit models predicting merger likelihood. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. Panels A, B, and C correspond to the Random Match; Industry, Size Match; and Industry, Size, B/M Match samples; respectively. Panel D uses the Industry, Size, B/M Match sample. The Random sample uses five randomly paired pseudo-targets (acquirers) for each acquirer (target) within a 2-digit SIC industry group. For the Industry, Size sample, we match to the five candidates with the smallest difference in book assets within a 2-digit SIC industry group. For the Industry, Size, B/M, sample, we match to the five candidates with the smallest standardized difference in size and book-to-market, weighed by industry standard deviation of those variables. *Political Distance* is the absolute value of the difference between acquirer and target *Democratic Affiliation.* In Panels A, B, and C, *Democratic Affiliation* is calculated using the number of employee donations. In Panel D, we measure political affiliations using donations originating from the zip-code where the firm is headquartered (*HQ Political Distance*). The dependent variable is an indicator variable equal to one for the acquirer-target firm pair and zero for the control firm-pairs.

The control variables include ***Book Assets***, ***Book to Market***, ***Sales Growth, Book Leverage,*** **and** ***Cash Ratio*** for each of the target and acquirer, as well as the deal-level variables ***Relative Size***, ***HQ Distance***, ***Cash Only***, **and** ***Diversifying***. The sample in Panels A-C includes 2,325 U.S. domestic mergers announced between 1985 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. In Panel D, the sample includes 3,655 mergers.

We require that both the acquirer and the target be publicly listed firms and that political donation data be available for both the acquirer and the target, except in Panel D where we require available data on political donations from the firm's headquarter zip-code. All variables are defied in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

Panel A: Random Match sample

Model	(1)	(2)	(3)	(4)
Political Distance	-0.692***	-0.346***	-0.346***	-0.421***
	(-7.54)	(-3.21)	(-3.22)	(-3.64)
Acquirer Democratic Affiliation	0.088	0.029	0.065	0.067
	(1.15)	(0.40)	(0.77)	(0.75)
Target Democratic Affiliation	0.086	0.186***	0.190***	0.241***
	(1.21)	(2.80)	(2.64)	(3.13)
Controls?	No	Yes	Yes	Yes
Industry×Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	19,704	17,904	17,532	15,421
Pseudo R^2	0.005	0.111	0.158	0.158

Panel B: Industry, Size Match sample

Model	(1)	(2)	(3)	(4)
Political Distance	-0.394***	-0.267***	-0.247**	-0.307***
	(-4.20)	(-2.71)	(-2.41)	(-2.80)
Acquirer Democratic Affiliation	0.047	-0.010	-0.022	-0.047
	(0.58)	(-0.14)	(-0.28)	(-0.56)
Target Democratic Affiliation	0.076	0.175***	0.201***	0.236***
	(1.07)	(3.00)	(2.90)	(3.20)
Controls?	No	Yes	Yes	Yes
Industry×Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	19,704	18,158	17,773	15,595
Pseudo R^2	0.002	0.035	0.135	0.128

Panel C: Industry, Size, B/M Match sample

Model	(1)	(2)	(3)	(4)
Political Distance	-0.621***	-0.337***	-0.313***	-0.347***
	(-6.75)	(-3.30)	(-2.96)	(-3.06)
Acquirer Democratic Affiliation	0.082	-0.010	-0.072	-0.051
	(1.07)	(-0.13)	(-0.88)	(-0.58)
Target Democratic Affiliation	0.091	0.216***	0.214***	0.236***
	(1.27)	(3.33)	(3.07)	(3.17)
Controls?	No	Yes	Yes	Yes
Industry×Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	19,704	17,892	17,516	15,399
Pseudo R^2	0.004	0.098	0.146	0.143

Panel D: Zip-code Donations and Industry, Size, B/M Match sample

Model	(1)	(2)	(3)	(4)
HQ Political Distance	-0.843***	-0.709***	-0.772***	-0.756***
	(-8.12)	(-5.92)	(-6.43)	(-5.96)
Acquirer HQ Democratic Affiliation	0.066	-0.017	-0.131	-0.151
	(0.84)	(-0.25)	(-1.45)	(-1.58)
Target HQ Democratic Affiliation	0.015	0.080	0.100	0.095
	(0.19)	(1.06)	(1.14)	(1.03)
Controls?	No	Yes	Yes	Yes
Industry×Year FEs?	No	Yes	Yes	Yes
Deal FEs?	No	No	Yes	Yes
Includes Hostile Bids?	Yes	Yes	Yes	No
Observations	40,059	33,676	32,280	28,943
Pseudo R^2	0.003	0.105	0.178	0.174

Table 4
Corporate Culture

This table presents estimates from conditional logit models predicting merger likelihood that control for measures of firm culture from Li, Mai, Shen, and Yan (2020). The five measures of culture are *Innovation*, *Integrity*, *Quality*, *Respect*, and *Teamwork*, and are constructed from earnings call transcripts. For each cultural measure, we calculate the cultural distance as the absolute value of the difference between the acquirer and target's value of that measure. We also calculate an overall cultural distance measure, *Aggregate Cultural Distance*, defined as the sum of the cultural distances calculated under each measure. *Political Distance* is the absolute value of the difference between acquirer and target *Democratic Affiliation* calculated using the number of employee donations. We standardize *Political Distance* and each cultural distance measure by subtracting their respective means and dividing by their respective standard deviations. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. We also exclude firm-years for which *Democratic Affiliation* measures are unavailable. We present results for the Industry, Size, B/M sample. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs.

The control variables include ***Book Assets***, ***Book to Market***, ***Sales Growth, Book Leverage,*** **and** ***Cash Ratio*** for each of the target and acquirer, as well as the deal-level variables ***Relative Size***, ***HQ Distance***, ***Cash Only***, **and** ***Diversifying***. The sample includes 464 U.S. domestic merger agreements announced between 2002 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids.

We require that both the acquirer and the target be publicly listed firms and that political donation and corporate culture data be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

Panel A: Individual Cultural Distance Measures

Model	(1)	(2)	(3)	(4)	(5)	(6)
Political Distance	-0.130**	-0.129**	-0.130**	-0.130**	-0.129**	-0.130**
	(-2.21)	(-2.18)	(-2.20)	(-2.20)	(-2.19)	(-2.21)
Innovation Distance		-0.075				
		(-1.18)				
Integrity Distance			-0.064			
			(-0.99)			
Quality Distance				-0.114		
				(-1.53)		
Respect Distance					-0.049	
					(-0.77)	
Teamwork Distance						0.108*
						(1.94)
Acquirer Democratic Affiliation	-0.153	-0.136	-0.151	-0.157	-0.156	-0.160
	(-0.83)	(-0.74)	(-0.82)	(-0.85)	(-0.84)	(-0.87)
Target Democratic Affiliation	0.123	0.126	0.125	0.127	0.125	0.120
	(0.83)	(0.84)	(0.83)	(0.85)	(0.84)	(0.80)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Deal FEs?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,738	4,738	4,738	4,738	4,738	4,738
Pseudo R-squared	0.141	0.142	0.141	0.142	0.141	0.142

Panel B: Combined Cultural Distance Measures

Model	(1)	(2)	(3)
Political Distance	-0.130**	-0.128**	-0.127**
	(-2.21)	(-2.17)	(-2.14)
Innovation Distance			-0.080
			(-1.29)
Integrity Distance			-0.070
			(-1.14)
Quality Distance			-0.116
			(-1.61)
Respect Distance			-0.020
			(-0.31)
Teamwork Distance			0.127**
			(2.26)
Aggregate Cultural Distance		-0.106	
		(-1.27)	
Acquirer Democratic Affiliation	-0.153	-0.144	-0.148
	(-0.83)	(-0.78)	(-0.80)
Target Democratic Affiliation	0.123	0.130	0.129
	(0.83)	(0.87)	(0.86)
Controls?	Yes	Yes	Yes
Industry×Year FEs?	Yes	Yes	Yes
Deal FEs?	Yes	Yes	Yes
Observations	4,738	4,738	4,738
Pseudo R-squared	0.141	0.142	0.145

Table 5
Political Polarization

This table presents estimates from conditional logit models predicting merger likelihood across subsamples with high vs. low levels of political partisanship. We consider two measures of political polarization. *High PCI* is an indicator variable equal to one if the value of *PCI,* constructed as the annual average of the Partisan Conflict Index from Azzimonti (2018), is greater than its sample median and zero otherwise. *High HPI* is an indicator variable equal to one if the value of *HPI,* the house partisanship index, is greater than its sample median and zero otherwise. *Political Distance* is the absolute value of the difference between acquirer and target *Democratic Affiliation* calculated using the number of employee donations. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. We also exclude firm-years for which *Democratic Affiliation* measures are unavailable. We present results for the Industry, Size, B/M sample. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs.

The control variables include ***Book Assets***, ***Book to Market***, ***Sales Growth, Book Leverage,*** **and** ***Cash Ratio*** for each of the target and acquirer, as well as the deal-level variables ***Relative Size***, ***HQ Distance***, ***Cash Only***, **and** ***Diversifying***. The sample includes 1,383 U.S. domestic mergers announced between 1995 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids.

We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

	High PCI = 0	High PCI = 1	Difference	High HPI = 0	High HPI = 1	Difference
Model	(1)	(2)	(2)-(1)	(3)	(4)	(4)-(3)
Political Distance	-0.241	-0.691***	-0.450*	-0.208	-0.726***	-0.518**
	(-1.49)	(-3.57)	(-1.78)	(-1.26)	(-3.85)	(-2.07)
Acquirer Democratic Affiliation	0.072	-0.185		0.050	-0.182	
	(0.55)	(-1.24)		(0.37)	(-1.24)	
Target Democratic Affiliation	0.218**	0.209*		0.219**	0.208*	
	(2.03)	(1.73)		(2.07)	(1.68)	
Controls?	Yes	Yes		Yes	Yes	
Industry×Year FEs?	Yes	Yes		Yes	Yes	
Deal FEs?	Yes	Yes		Yes	Yes	
Observations	7,893	5,654		7,905	5,642	
Pseudo R-squared	0.173	0.116		0.168	0.120	

Table 6
Economic Recessions

This table presents estimates from conditional logit models predicting merger likelihood across NBER recessions and non-recession periods. *Political Distance* is the absolute value of the difference between acquirer and target *Democratic Affiliation* calculated using the number of employee donations. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. The control variables include ***Book Assets***, ***Book to Market***, ***Sales Growth***, ***Book Leverage***, **and** ***Cash Ratio*** for each of the target and acquirer, as well as the deal-level variables ***Relative Size***, ***HQ Distance***, ***Cash Only***, **and** ***Diversifying***. The sample includes 1,581 U.S. domestic mergers announced between 1985 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

	Recession = 0	Recession = 1	Difference
Model	(1)	(2)	(2)-(1)
Political Distance	-0.395***	0.190	0.585
	(-3.36)	(0.42)	(1.25)
Acquirer Democratic Affiliation	-0.053	-0.110	
	(-0.59)	(-0.26)	
Target Democratic Affiliation	0.242***	0.206	
	(3.15)	(0.66)	
Controls	Yes	Yes	
Industry×Year FEs?	Yes	Yes	
Deal FEs?	Yes	Yes	
Observations	14,283	1,116	
Pseudo R-squared	0.139	0.224	

Table 7
Integration

This table presents estimates from conditional logit models predicting merger likelihood, which are estimated separately across deals involving high vs. low levels of post-merger integration. *Integration* is an indicator variable equal to one for mergers where the DEF14A or post-merger 10K/Q filing mentions the words "integrate" or "integration" more frequently than the median deal and zero otherwise. *Political Distance* is the absolute value of the difference between acquirer and target *Democratic Affiliation* calculated using the number of employee donations. To construct the sample, we follow Bena and Li (2014) and match each acquirer (target) with up to five pseudo-targets (acquirers) in the year preceding the merger announcement. We exclude firms that have been acquirers or targets in the three years preceding the merger announcement. We also exclude firm-years for which *Democratic Affiliation* measures are unavailable. We present results for the Industry, Size, B/M sample. The dependent variable is equal to one for the acquirer-target firm pair and zero for the control firm-pairs. The control variables include ***Book Assets*****,** ***Book to Market*****,** ***Sales Growth, Book Leverage,*** **and** ***Cash Ratio*** for each of the target and acquirer, as well as the deal-level variables ***Relative Size*****,** ***HQ Distance*****,** ***Cash Only*****, and** ***Diversifying***. The sample includes 452 U.S. domestic merger agreements announced between 1993 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We exclude hostile bids. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Pseudo R^2 is within groups. Significance: * p <10%, ** p < 5%, *** p < 1%.

	Integration = 0	Integration = 1	Difference
Model	(1)	(2)	(2)-(1)
Political Distance	-0.523	-1.174***	-0.650
	(-1.62)	(-2.99)	(-1.28)
Acquirer Democratic Affiliation	0.087	-0.075	
	(0.35)	(-0.22)	
Target Democratic Affiliation	0.253	0.185	
	(1.14)	(0.76)	
Controls?	Yes	Yes	
Industry×Year FEs?	Yes	Yes	
Deal FEs?	Yes	Yes	
Observations	2,222	2,249	
Pseudo R-squared	0.235	0.229	

Table 8
Merger Completion and Hostile Takeovers

This table presents estimates from conditional logit regressions predicting the likelihood of a hostile takeover (Columns 1 and 2) and the likelihood of merger completion (Columns 3 and 4). *Hostile* is an indicator variable equal to one if the announced merger is a hostile takeover and zero otherwise. *Withdrawn* is an indicator variable equal to one if the merger is withdrawn and zero otherwise. *Political Distance* is the absolute value of the difference between acquirer and target *Democratic Affiliation* calculated using the number of employee donations. The control variables include ***Book Assets*, *Book to Market*, and *Cash Ratio*** for each of the target and acquirer, as well as the deal-level variables ***Relative Size*, *HQ Distance*, *Cash Only*, and *Diversifying***. The sample includes 2,325 U.S. domestic merger agreements announced from 1985 to 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report z-scores in parentheses. Significance: * p <10%, ** p < 5%, *** p < 1%.

Variables	Hostile		Withdrawn	
	(1)	(2)	(3)	(4)
Political Distance	0.523**	0.543**	0.480**	0.440*
	(2.02)	(2.08)	(2.14)	(1.94)
Acquirer Democratic Affiliation	0.133	0.153	0.438**	0.430**
	(0.58)	(0.65)	(2.20)	(2.10)
Target Democratic Affiliation	-0.550***	-0.452**	-0.238	-0.136
	(-2.64)	(-2.09)	(-1.32)	(-0.73)
Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	2,016	2,016	2,016	2,016
Pseudo R^2	0.119	0.106	0.081	0.079

Table 9
Merger Announcement Returns

This table presents estimates from OLS regressions explaining merger announcement returns. The dependent variable is the value-weighted total cumulative abnormal return (CAR) in the days surrounding the merger announcement date. *Political Distance* is the absolute value of the difference between acquirer and target *Democratic Affiliation* calculated using the number of employee donations. In Panel A, we calculate CARs using returns in excess of the market. In Panel B, we calculate CARs using the Capital Asset Pricing Model. In Panel C, we calculate CARs using the Fama-French Three Factor Model with Momentum. The control variables include ***Book Assets*****,** ***Book to Market*****,** ***Sales Growth*****,** ***Book Leverage*****, and** ***Cash Ratio*** for each of the target and acquirer, as well as the deal-level variables ***Relative Size*****,** ***HQ Distance*****,** ***Cash Only*****, and** ***Diversifying***. The sample includes 2,325 U.S. domestic merger agreements announced from 1985 to 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report *t*-statistics in parentheses. Significance: * p <10%, ** p < 5%, *** p < 1%.

Panel A: Market Excess Returns

Event Window	[-1, 1]		[-1, 5]	
Model	(1)	(2)	(3)	(4)
Political Distance	-0.016**	-0.015**	-0.017**	-0.015*
	(-2.31)	(-2.16)	(-2.00)	(-1.82)
Acquirer Democratic Affiliation	0.014**	0.013**	0.009	0.007
	(2.24)	(2.07)	(1.19)	(0.92)
Target Democratic Affiliation	0.005	0.001	0.004	-0.001
	(0.99)	(0.22)	(0.71)	(-0.21)
Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	1,593	1,593	1,593	1,593
Adjusted R^2	0.090	0.110	0.048	0.070

Panel B: CAPM Excess Returns

Event Window	[-1, 1]		[-1, 5]	
Model	(1)	(2)	(3)	(4)
Political Distance	-0.013**	-0.013*	-0.013*	-0.012
	(-2.00)	(-1.87)	(-1.72)	(-1.55)
Acquirer Democratic Affiliation	0.013**	0.012*	0.013*	0.011
	(2.08)	(1.95)	(1.83)	(1.56)
Target Democratic Affiliation	0.007	0.003	0.004	-0.002
	(1.32)	(0.56)	(0.61)	(-0.26)
Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	1,593	1,593	1,593	1,593
Adjusted R^2	0.090	0.111	0.050	0.067

Panel C: Fama French Three Factor Model with Momentum Excess Returns

Event Window	[-1, 1]		[-1, 5]	
Model	(1)	(2)	(3)	(4)
Political Distance	-0.014**	-0.013*	-0.014*	-0.013
	(-2.03)	(-1.91)	(-1.82)	(-1.63)
Acquirer Democratic Affiliation	0.013**	0.012**	0.013*	0.011
	(2.17)	(2.02)	(1.84)	(1.56)
Target Democratic Affiliation	0.007	0.003	0.004	-0.001
	(1.32)	(0.50)	(0.76)	(-0.20)
Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	1,593	1,593	1,593	1,593
Adjusted R^2	0.089	0.110	0.049	0.070

Table 10
Post-Merger Performance

This table presents estimates from OLS regressions explaining firms' industry-adjusted return on assets and buy and hold abnormal returns. In columns 1 and 2, the dependent variable is the combined company's average *Industry-adjusted ROA* in the three years following merger completion (*3-year Industry-adjusted ROA*). In columns 3 and 4, the dependent variable is the 3-year Buy-and-Hold Abnormal Returns (*3-year BHAR*) following the merger announcement. We calculate BHARs using returns in excess of those predicted by the Capital Asset Pricing Model (CAPM), winsorized at the 1st and 99th percentiles. Control variables are the acquirer's ***Industry-Adjusted ROA*** in the year before the merger announcement, ***Relative Size***, ***HQ Distance***, ***Cash Only***, **and** ***Diversifying***. The sample includes 2,264 U.S. domestic merger agreements announced between 1985 and 2021 with a transaction value of at least $10 million from the Thomson Reuters Securities Data Company (SDC) Platinum database. We require that both the acquirer and the target be publicly listed firms and that data on employee political donations be available for both the acquirer and the target. All variable definitions are given in Appendix A. We report *t*-statistics in parentheses. Significance: * p <10%, ** p < 5%, *** p < 1%.

Variable	3-year Industry-adjusted ROA		3-year BHAR	
Model	(1)	(2)	(3)	(4)
Political Distance	-0.025**	-0.021**	-0.480**	-0.356*
	(-2.53)	(-2.15)	(-2.37)	(-1.76)
Acquirer Democratic Affiliation	0.009	0.010	-0.003	-0.037
	(0.99)	(1.08)	(-0.01)	(-0.20)
Target Democratic Affiliation	0.000	-0.001	-0.063	-0.157
	(0.04)	(-0.17)	(-0.41)	(-1.00)
Controls?	Yes	Yes	Yes	Yes
Year Fixed Effects?	No	Yes	No	Yes
Observations	1,711	1,711	1,578	1,577
Adjusted R^2	0.246	0.265	0.021	0.051